



Smart Protection of Cotton Crops: A Review of IoT Sensor Networks and ML-Based Pest Decision Support Systems

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Abstract— Cotton is found to be a globally significant commercial crop, with India contributing approximately 22% of the world's production and often referred to as “white gold”. But cotton is highly vulnerable to insect damage, so early diagnosis is necessary to reduce disease transmission and enhance treatment effectiveness. Traditional methods are labour-intensive, which often results in delayed responses and significant crop losses. This study explores various pests found in India and their management in the cotton field by using different sensors and a smart detection-response system utilising IoT sensor networks and machine learning to monitor and classify pests, specifically targeting the Bollworm complex and whiteflies. The proposed architecture comprises different sections: Field traps, Gateway, central control system, Drone spraying, and Farmer sections, integrating motion-detecting sensor traps, communication modules, and an autonomous aerial vehicle for targeted pesticide spraying. The proposed system optimises flight paths for rapid response and includes protocols for handling false alarms, leveraging camera-equipped drones and human assistance. While the integration of IoT offers precision and accuracy, challenges such as hardware durability in harsh environments, networking interference in rural areas, and the need for farmer education remain critical hurdles for widespread adoption.



Keywords— Cotton pests, Drone spraying, IoT system, Sensors.

I. INTRODUCTION

Agriculture forms the economic backbone of many nations with cotton as the widely grown crop. However, its economic yield is severely affected by insect pests, making the implementation of technologies in the field essential. India is the second largest producer of cotton after China, accounting for approximately 22% of the world's cotton production, which is estimated at 5.79 million tons [6]. There is a high risk of damage in the cotton field due to insects. The early loss of leaves or the development of diseases impacts cotton yield, so early diagnosis of plant illnesses is essential for reducing disease transmission and enhancing effective treatment strategies. With the increasing population demand for food and crop also increases but pests remain the enemies of crop. At the same

time climate change and water scarcity are the reasons for decrease in fertile land [20]. To attain cotton in large quantities we have to make effective plans for its prevention from pests [5,11].

The traditional methods of disease identification are labour-intensive and often delayed, leading to significant crop losses. Many organs are harmed by cotton diseases during different growth periods and some are infected with vascular diseases [4]. Recent advancements in IoT and artificial intelligence (AI) provide an opportunity to develop a smart system capable of monitoring and detection of diseases. In this study, an overview of previous research on sensor networks and machine learning techniques for classifying various diseases and pests has been presented.

II. SCOPE OF THE REVIEW

This review focuses on the detection and management of cotton pests using sensors that specifically target the Bollworm complex and sucking pests such as whiteflies for early detection and monitoring in the field. This study intended to understand the potential of the IoT system, its associated challenges, and its success in the cotton environment. Furthermore, we evaluate the role of Edge Gateways (such as Zigbee) and autonomous response units, such as UAVs, in creating a closed-loop precision management system. The existing literature was searched using the following keywords: “cotton pests”, “sensors”, “IoT system”, and “Drone Spraying”. The remainder of this review is organised as follows: Section 3 explores the role of IoT in agriculture and different types of sensors which can be used for pest detection; Section 4 details the specific prototype architecture for cotton pest detection; Section 5 outlines the smart response system and comparison between communication modules; and Section 6 discusses the prevailing hardware, networking, and educational challenges in the field.

III. IoT IN AGRICULTURE

The “Internet of Things”(IoT) in agriculture uses connected devices such as automated drones and field sensors to optimize and monitor agricultural practices in real time. Current literature review typically divides an IoT system into four different tiers [1].

- Sensing Tier:- It senses the change in the environment .
- Transport/Gateway Tier:- It facilitates communication between two different hardware technologies.
- Processing Tier:- Analyzes or processes the incoming data.
- Application Tier:- It provides the user interface for crop monitoring and control operations.

Different sensors and their possible use in IoT based agriculture systems are provided in review[14].

3.1. Different Types of Sensors

3.1 Low-Power Cameras & Sensors-

- Farmers can install a low-cost image sensor in traps with pheromones or male sex attractants that captures the images of pests in it and sends it to a centralized platform wirelessly.
- Based on the number of insects present in traps, the farmers determine the location of insect infestation and take steps to remove them from fields.
- Low-power image sensors only click random images of insects that are visible to the naked eye.

3.2 High Power Thermal Sensors-

- THERMOGRAPHY is a method that uses thermal and infrared sensors to measure the amount of light reflected by a surface [3].
- Every surface reflects a distinct amount of light energy which is also called its spectral signature.
- Plants and soil have a special spectral spectrum that is pre-recorded in spectrometers.
- In case of pathogens covering the surface of plant leaves, the spectrum range of the plant will change, indicating an attack by the pests.

3.3 Fluorescence Image Sensing-

- In this method the amount of chlorophyll present in a plant is measured based on its change in fluorescence parameters.
- An optimal camera captures an image of a plant leaves and then compares it with existing images of a healthy leaf.
- Change in chlorophyll patterns indicates the presence of pathogens and pests.

3.4 Acoustic Sensors-

- Detecting bugs and rodents through sound detection is another effective way to ensure plant quality.
- Wireless acoustic sensors situated at random locations in a field can pick up sound waves of insects.
- Locations with high sound waves indicate a high concentration of bugs.
- A farmer can thus spray pesticides on these locations to ensure the quality of crops.

3.5 Gas Sensors-

- Plants, when stressed produce specific volatile chemical compounds.
- These compounds differ based on the stress they feel.
- Compounds secreted due to environmental changes will be different then the compounds emanated due to pest infestation.
- Sampling is required to collect volatile compounds for data analysis.

IV. IoT-BASED SMART DETECTION AND RESPONSE SYSTEM ARCHITECTURE

Pests account for an estimated 20% to 40% of global crop losses each year, as reported by the FAO [9,17]. Majorly the cotton field is infested with "Pink Bollworm" pests. Disease in plants influences the economic status and the speed at which production takes place. However, the human method

of identifying such diseases is likely to be inaccurate since most organisms that cause the diseases cannot be easily seen with the naked eye [16]. Recent prototype systems utilize a combination of motion - sensing hardware and and communication module like zigbee which is further connected with a micro controller or Arduino [1]. When field movement is detected, the sensors generate and transmit data packets in a hexadecimal format. These data packets crucially contain the geographic coordinates of the

sensors, allowing gateway devices to precisely map the location of the potential pest threat.

4.1 How the system actually works-

The system first identifies the pest's presence near the crop and then sends the detection to the base station which is present in the centre of the field via a communication module. In response, the system attempts to destroy it by a targeted spray through a drone.

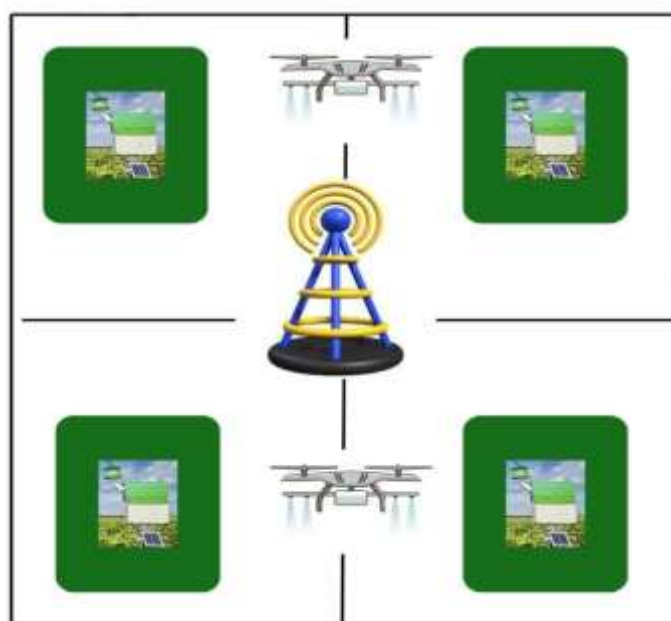


Fig 1: Architecture of the system

4.2 IoT-Based Cotton Pest Detection-

The system includes five elements, with the first level handling the identification of data on the insects, while the second level deals with the analysis of the data collected in the first level. As far as the third level is concerned, the analysis and transmission of data to the sensor sending the data to the drone will be carried out here. Finally, in the fourth level, drones will deal with spraying the area after receiving the signals.

Field Layer: This level is one of the easiest in the cotton plantation. It involves both sensors and communication modules. This level is responsible for detection of the insects by the sensors and transmission of the information to the base station through the communication module. Besides the sensors, the model also has another transmitter called ZED. The most important thing about this level is that the coverage range is from 10-100meters with a data rate of 250 kbps. However, using LoRA can enhance our area of coverage.

Gateway Layer: The primary purpose of this tier is to receive data generated by the sensors and take appropriate

action. Based on the insect detection alerts, it determines the specific target locations for the drones. For example, if one sensor sends a single alert while another transmits continuous signals, the system will prioritize directing the drones to the source of the repeated messages.

Control Layer: This tier operates by analyzing the incoming data packets from the sensor network. The system performs several key evaluations based on this information: Identifying which specific cluster is experiencing the highest insect activity and investigating the potential causes. Assessing how the crop quality in the highly infested cluster might differ from less affected areas. Determining if an increased volume of pesticide spray is required to effectively manage the pests in these high-activity clusters.

Response Layer: Operating as the active defense mechanism for the entire setup, this tier is crucial for pest mitigation. It incorporates the drones and ZigBee Controller (ZC) modules, utilizing the specific coordinates transmitted by the sensors to guide the drones for targeted pesticide application. If the pests have migrated by the time the drone

reaches the designated coordinates, the system is designed to expand the spraying radius to cover surrounding adjacent areas. This workflow is illustrated in Figure 2 below.

Farmer Layer: This tier consists of a dedicated web dashboard that allows farmers to monitor the system's daily

operations. For example, the interface provides comprehensive daily reports detailing the frequency of sensor detection alerts alongside the total number of drone spraying missions executed. The comprehensive flow of how the system receives and acts upon these signals is depicted in the flowchart below.

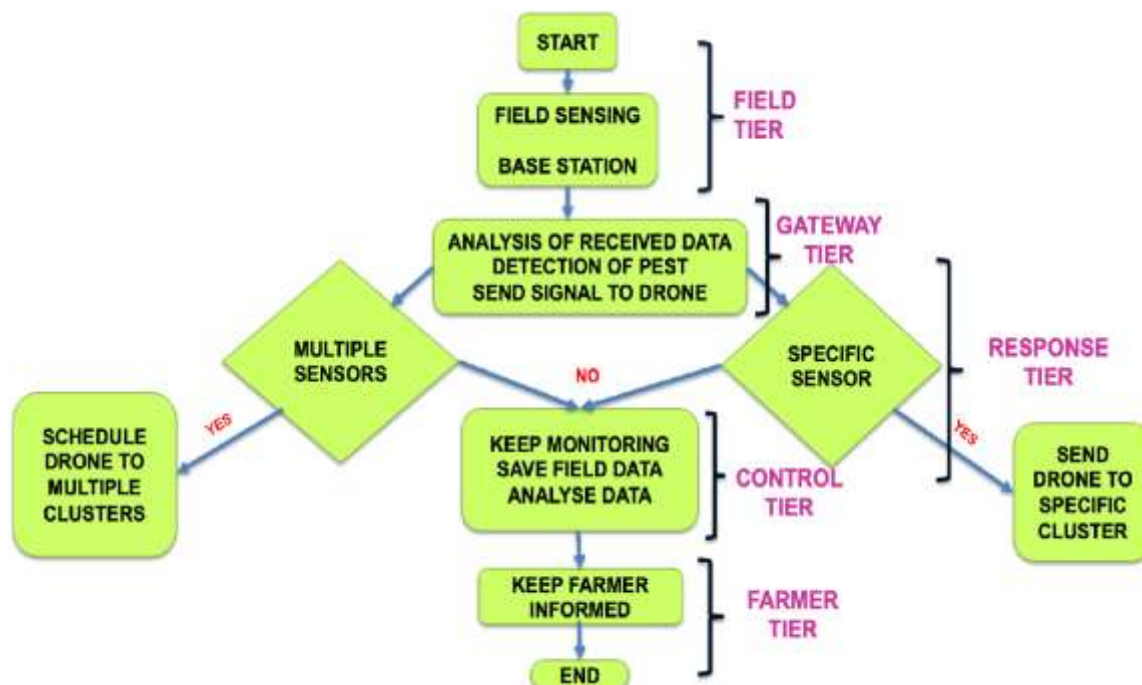


Fig 2: Smart Detection Response System

V. SMART RESPONSE SYSTEM

The simulation area is systematically divided into equal clusters, with IoT nodes evenly distributed throughout each section. While the transmission power remains consistent across all individual field sensors, the gateway node is equipped with an extended communication range. This broad coverage allows the gateway to simultaneously communicate with the entire sensor network and relay detection alerts directly to the drones.

Furthermore, the central base station maintains a precise database of coordinates for every cluster. When a pest alert is received, the base station instantly identifies both the specific sensor and its corresponding cluster. To ensure a rapid response, coordinate-based, low-altitude flight paths have been programmed, allowing the drone to navigate to the target zone in the minimum possible time. Because the flight speed of targeted pests, such as moths, is relatively slow compared to the rapid deployment speed of the unmanned aerial vehicles, the system can effectively intercept them before they migrate. The rise of the camera and connectivity in computer vision presents an opportunity to utilize computer vision as another tool for automated monitoring of pests in modern agricultural operation [15].

5.1 Algorithm Operations and processing

The drone movement prediction algorithm is structured into three primary phases. During the initial phase, all network devices activate to establish immediate synchronization with one another. This initialization is isolated as a distinct step because establishing wireless communication involves an inherent time delay; devices must first exchange initial data packets, known as beacons, to signal their readiness before any subsequent data transmission can occur.

In the second part, three cases are possible:

Case 1: Upon detecting insect activity, field sensors transmit alerts to the central base station. Subsequently, the control unit relays precise geographic coordinates to the autonomous drone, directing it to the infested zone for mitigation. Once the targeted spraying mission is finalized, the drone evaluates whether additional pest detection signals have been received from other field clusters. If concurrent threats are identified, the aerial vehicle proceeds to treat those specific locations before returning to its docking hangar.

Case 2: In this situation, if the base station receives only a solitary notification, the system may initiate a recall

protocol for the deployed drone. This procedure is implemented to mitigate the impact of potential false alarms, as a single isolated message might not signify a genuine pest infestation requiring chemical intervention.

Case 3: If the base station receives messages from different clusters simultaneously, the base station will instruct the drone to start again with the process of choosing the required cluster to spray before making a decision about which to spray first. To ensure that all spraying occurs simultaneously, more drones can be used in this process. But, if the messages keep arriving from different clusters, then the base station may dispatch a camera drone to find out why it has started receiving messages from that particular area. It might be that there is no bug, just that the message sender itself is faulty.

The concluding segment of the algorithm functions as a robust protocol for managing persistent technical anomalies. In scenarios where field sensors maintain a continuous stream of alerts following both chemical mitigation and visual verification by camera drones, the system mandates a transition to manual oversight. Ultimately, a designated human technician is sent to the specific coordinates for a physical evaluation. Any identified irregularities are relayed to the central control station, ensuring that immediate corrective measures can be implemented on-site.

VI. CHALLENGES OF INTERNET OF THINGS IN SMART AGRICULTURE

According to the research and its increasing density, we can say that before artificial intelligence, IoT is the best technology that we have. It may take another 30 to 40 years to integrate AI into almost every field, or it may be a possibility that we cannot achieve AI with the same level of intelligence as human beings (Jadon et al., 2022). Therefore, we are relying on this IoT technology for the next 30 to 40 years, particularly in countries with less developed economies or large populations, such as India, Brazil, and Malaysia, where agriculture is a major economic aspect; it may take more time. In the agricultural domain, the main challenge is to present the new information and research to the farmers so that they can leverage the power of technologies to improve their agricultural practices and thereby the production [19].

Hardware Components Challenges:- The development of a system requires a lot of hardware components, most of which are required to be exposed to harsh environments for most of their life. Development of such hardware that can sustain in such a harsh environment is really a point of concern. The harsh environment can destroy the electronic

circuit, and the system will not perform or may lead to an adverse effect on the field.

Organizational Challenges:- The agricultural organizations are meant to exchange information and transport goods. IoT brings accuracy in the delivery of these agricultural products [10]. In this respect, cloud computing provides the best services such as app development tools, efficient storage and resources. The Internet of Technology-based systems provides huge data that needs to be transferred and thus requires a huge cost.

Networking Challenges:- The IoT uses many networking protocols like Internet connectivity, Bluetooth and Wi-Fi. The operation of unlicensed devices using similar protocols causes interference and may cause problems in the operation of these IoT-based agriculture technologies [8]. Internet connectivity and network issues are always experienced in rural areas, and agricultural fields are found mostly in rural areas.

Challenge to Educate Farmers:- The IoT-based systems are very complicated and become more robust when it comes to IoT-based agriculture technology, but their success depends on farms. Farmers must be able to perform their tasks using these new technologies, but without education, they are not able to do that. Spending time learning these new technologies will cost them a huge loss in their profession. The uneducated farmers need more time to learn this technology.

VII. CONCLUSION

Integrating the implementation of IoT sensing frameworks alongside decision-making processes which depend on ML-based tools becomes another key element that requires attention in order to ensure efficient cotton pest management through effective implementation of precision agriculture technologies rather than the traditional techniques. The major benefit of using the proposed Decision Support System is the ability of tracking harmful pests accurately in real-time, meaning that there will not be the necessity of applying pesticides in case if the problem appears in an inappropriate manner as a result of human errors. At the same time, there are some potential challenges which should be taken into account prior to the implementation of the innovation, including weather conditions, network instability, as well as financial matters. Recommendations for further research about applying the system may refer to the protection of other cash crops, developing more precise algorithms considering multiple drones along with the field alert situation, as well as the development of AI algorithms on the edge device located in the camera.

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